Dynamic temporary blood facility location-allocation during and post-disaster periods

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Abstract

The key objective of this study is to develop a tool (hybridization or integration of different techniques) for locating the temporary blood banks during and post-disaster conditions that could serve the hospitals with minimum response time. We have used temporary blood centers, which must be located in such a way that it is able to serve the demand of hospitals in nearby region within a shorter duration. We are locating the temporary blood centres for which we are minimizing the maximum distance with hospitals. We have used Tabu search heuristic method to calculate the optimal number of temporary blood centres considering cost components. In addition, we employ Bayesian belief network to prioritize the factors for locating the temporary blood facilities. Workability of our model and methodology is illustrated using a case study including blood centres and hospitals surrounding Jamshedpur city. Our results shows that atleast 6 temporary blood facilities are required to satisfy the demand of blood during and post-disaster periods in Jamshedpur. The results also show that that past disaster conditions, response time and convenience for access are the most important factors for locating the temporary blood facilities during and post-disaster periods.

Keywords: Facility Location, Temporary Blood Center, Diaster Relief Operations, Bayesian Belief Networks, Tabu search heuristic, Minimax

1. Introduction

A ‘disaster’ is referred to an unconventional occurrence that causes damage, destruction, ecological disruption, loss of human life, human suffering, deterioration of health and health services on a scale sufficient to warrant an extraordinary response from outside the affected community or area (World Health Organization, 2002; Najafi et al. 2013; Wang et al. 2016). Such events may include natural disasters (e.g. earthquakes, hurricanes, tornadoes, volcanic eruptions, wild fires, floods, blizzard and drought), and man made disruptions (e.g. terrorism, chemical spills and nuclear accidents) (Jabbarzadeh et al. 2012; Jabbarzadeh et al. 2014; Ramezanian & Behboodi, 2017). All the above-mentioned disasters have significant harmful effects in terms of human injuries and planning for the supply of blood during and after disasters is very much important as sudden boost in demand occurs (Schultz et al. 1996; Hess and Thomas, 2003). Recent disasters (e.g. Massive Nepal earthquake in

2015, Great East Japan earthquake in 2011, Tsunami in 2004, Sichuan earthquake in 2008, Chennai floods in 2015) have shown how external disruptions can affect the efficient supply of blood (Jabbarzadeh et al. 2014). Due to the inefficient design of blood supply chain only 23% of the demand was fulfilled during Bam earthquake of Iran in 2003, which leads to high mortality rate (Abolghasemi et al. 2008). As disasters are highly unpredictable, the preparedness for effective blood supply to locate a number of blood facilities may also incur significant costs. While designing blood supply chain, the storage temperature range and the expiry dates of blood and blood products should be taken into account to avoid obsoletes (Jabbarzadeh et al. 2014).

The management of proper supply of safe blood and blood products has become a national importance in almost all countries due to its concern for humankind (Beliën & Forcé, 2012). Eventhough, there are technological advancements in the field of medicine, there will be need always for blood and its derived products as there is no exact substitute for human blood (Jabbrzadeh et al. 2014; Delen et al. 2011). Matching the supply and demand of blood during natural disaster is difficult as blood products are perishable and its supply is fairly irregular while its demand is stochastic. Certain characteristics make blood as a unique perishable product such as life of red blood cells and platelets, availability of donor population; pre-screening tests; guidelines for supply of safe products without infection (Esmaeilikia et al. 2016).

The blood facility or blood center is the location for the collection, receipt, processing, testing, storing and distribution of blood (World Health Organization, 2010). The blood facility must collect and store the blood in a proper way from the eligible donors, because when the need arises and if the blood is not available at that time, there will be serious consequences of mortality (Beliën & Forcé, 2012; Delen, 2011; Stanger, 2012). The blood center should accommodate a static blood collection facility while also coordinating dynamic mobile collection facilities along with specialist laboratory and research facilities. The main aim of blood supply network design is to determine the optional location, capacity of blood facilities, forecast the demand efficiently and to satisfy the same at a lower cost (Esmaeilikia et al. 2016; Fahimnia et al. 2017; Zahiri & Pishvaee, 2017). While static supply network design in a ordinary situation assume that the location and capacity of facilities would remain unchanged, however, dynamic network design during disasters needs frequent updates as per the demand fluctuations considering adjustments in location and capacity of facilities in the post disaster zone (Jabbarzadeh et al. 2014; Melo et al. 2009; Sheu, 2010; Dubey & Gunasekaran, 2016).

Disaster situations mandate high demand of blood units, however,the inventory left with hospitals alone is not sufficient. Over the occurrence of the events the demand for blood is different. For instance, the demand of blood during first 24 hours of disaster is very high comparing to the second or third day of disaster (Jabbarzadeh et al. 2014). During and post-disaster periods, temporary blood facilities can be easily moved to different locations for collecting blood from eligible donors. So our model is based on the multi-period (during and post-disaster) dynamic facility location problem to meet the needs of disaster relief using temporary blood facility. Regardless of the rich literature on facility location and allocation problems the research on dynamic blood facility location and allocation during disaster is limited in the emerging economies context (Jabbarzadeh et al. 2014; Ahmadi-Javid et al. 2017; Salman and Yücel, 2015). So, there is a need to propose a new approach for determining the location of facilities for proper supply of blood and blood products during and post-disaster periods in emerging economics. This motivates us to work in the area of dynamic temporary blood facility location and allocation decisions during and post-disaster periods in the Indian context.

The key objective of this research is to develop a tool for locating the temporary blood banks that could serve the demand of nearby hospitals at high response rate during and post-disaster periods. Our goal is to make transport distance minimal to hospitals, but at the same time to cover as much blood donors as possible. Considering all these constraints, we have proposed a methodology to solve the problem based on Tabu search heuristics. Here we have taken a case of multi facility location with mini-max with Euclidean distances. We have also determined the optimal number of temporary blood centers on the basis of population and using the different cost components such as fixed cost, transportation cost and maintenance cost. Also, we have considered Bayesian belief network for determining and ranking the important factors that could affect the location of temporary blood facility by considering two different cases: (1) when there is no presence of industries in the city; (2) when there is presence of industries in the city. For the better understanding of the proposed mechanism a case study is presented for the blood centers and hospitals for the Jamshedpur city.

The remainder of the paper is organized as follows. Section 2 briefs the model formulation for facility location decisions. Section 3 provides a background for determining the optimal number of temporary blood facility during and post-disaster periods. The Bayesian belief network model is presented in Section 4. The application of the proposed model in a real world context is presented in Section 5. The discussion of results is presented in section 6. Concluding remarks and directions for further research in the area are presented in Section 7.

2. Literature review

2.1 Facility location allocation models

Over the last three decades, we have seen a rapid evolution of academic research on facility location (Esmaeilikia et al. 2016; Jabbarzadeh et al. 2014; Melo et al. 2009). The facility location problem is mainly concerned with the identification of best geographical setting for locating one or more facilities to minimize transportation costs (Jabbarzadeh et al. 2014). Facility location models can be classified as follows

- Number of new facilities: Single, Multiple
- Location Capacity: Capacitated, Uncapacitated
- Solution space: Continuous, Discrete
- Distances Measures: Rectilinear, Euclidian, Actual
- Objective Functions: Minisum, Minimax, Maximin

We have conducted a thorough review of literature on general facility-location allocation problems and tabulated the various methodologies applied in various fields in Table 1. Literature reveals that there is ample research on facility location and many models and methodologies have been developed by various researchers to formulate and solve various location problems (see Table 1). However, most of the prior research on facility location has failed to address the special characteristics of large-scale emergency situations that arise when locating facilities during emergent conditions such as earth quakes, terrorist attacks etc., (Jia et al. 2007). In section 2.2, we survey facility location problems that address large-scale emergent situations.

Table 1: Facility location-allocation models

Citation	**Overall research focus**	**Methodology used**
Melo et al. (2009)	Facility location and supply chaijn management	Literature review
Korupolu et al. (2000)	Local search heuristics for several NP-hard facility location problems	Approximation algorithms
Klose and Drexl (2005)	Facility location models for distribution system design	Mixed-integer programming
Kahraman et al. (2003)	Facility location selection problem	Blin's fuzzy relations, weighted goals method, fuzzy AHP
Balcik and Beamon (2008)	Facility location in humanitarian relief operations	Mathematical model
Snyder and Daskin (2005)	The expected failure cost case in facility location	P-median problem, uncapacitated fixed charge problem, optimal Lagrangian relaxation algorithm
Lu and Bostel (2007)	Facility location for a remanufacturing network	Lagrangian heuristics
Melo et al. (2006)	Multi-commodity capacitated facility location for strategic supply chain planning	Mathematical modeling
Jia et al. (2007)	Facility location of medical services for large scale emergencies	P-median, P-center
Chou et al. (2008)	Facility location selection problem	Fuzzy set theory, factor rating system, simple additive weighting
Ertuğrul and Karakaşoğlu (2008)	Facility location selection problem	Fuzzy AHP, Fuzzy TOPSIS
Hochreiter and Pflug (2007)	Financial scenario generation for facility location decision	Stochastic programming
Gao (2012)	Uncertain models for single facility location problems on networks	Uncertain programming
Cui et al. (2010)	Reliable facility location design under the risk of disruptions	Mixed integer programming, Lagrangian relaxation, continuum approximation model
Amin and Zhang (2013)	Facility location model for closed loop supply network under uncertain demand and return	Mixed-integer linear programming, Stochastic programming
An et al. (2017)	Capacitated facility location problem	Linear programming
Rahmani and MirHassani (2014)	Capacitated facility location problem	Hybrid firefly-genetic algorithmm
Ahmadi-Javid (2017)	Healthcare facility location	Literature review
Bilir et al. (2017)	Competitive facility location model for supply chain network	Mixed integer linear programming, multi-objective optimization
Tran et al. (2017)	Single-source capacitated facility location problem	Hyper graph multi exchange heuristics
Guo et al. (2017)	Two-stage capacitated facility location problem	Hybrid evolutionary algorithm
Maass et al. (2016)	Mitigating hard capacity constraints with inventory in facility location modeling	Mixed-integer programming

2.2 Facility location allocation models for disaster relief operations

As the number of disasters and the people affected by disasters have increased over recent years, literature reveals that lot of researchers have been working in different aspects of disaster relief operations (Özdamar and Ertem, 2015; Roh et al. 2015; Richardson et al. 2016; Papadopoulos et al. 2017). We have conducted a thorough review of literature on facility-location allocation problems in large-scale emergency situations such as earthquake, terrorist attack and tabulated the same in Table 2.

Table 2: Facility location-allocation models for disaster response

Citation	Overall Research Focus	Methodology Used
Chen and Yu (2016)	Temporary facility location for emergent medical services	Integer programming, network based clustering, k-Medoids
Salman and Yücel (2015)	Emergency facility location under random network damage	Scenario generation algorithm, Tabu search heuristic
Akgün et al. (2015)	Risk based facility location in disaster management	Fault tree analysis
Abounacer et al. (2014)	Location-transportation problem in disaster response	Multi-objective combinatorial optimization, Epsilon-constraint method
Barzinpour and Esmaeili (2014)	Relief chain location distribution model for urban disaster management	Goal programming
Rennemo et al. (2014)	Facility routing model for disaster response planning	Stochastic programming
Marcelin et al. (2016)	Accessability of hurricane relief facility for aging and general population	p-Median modeling
Ghezavati et al. (2015)	Reliability of facilitily location under disaster situation	Chance-constrained programming and robust optimization
Hadiguna et al. (2014)	A web based decision support system for disaster logistics	Object-oriented programming
Zhen et al. (2015)	Disaster relief facility location design in metropolises	Lagrangian relaxation
Cheraghi and Hosseini-Motlagh (2017)	Optimal blood transportation in disaster relief	Chance-constrained programming

Determining the locations of temporary blood collection facilities for maintaining proper supply of blood to be used during a disaster or post-disaster periods is a strategic decision that directly affects the success of disaster response operations. Locating such facilities close to the disaster-prone areas is of utmost importance to minimize response time. Our main aim in this research is to minimize the transportation time from the temporary blood facility to the nearby hospitals. Also, we have to satisfy the demand of the nearby hospitals during and post-disaster periods by collecting as much blood from the eligible donors. Also, we have to find the optimal number of temporary blood facilities to be located in disaster prone area. In our study, we have taken a case of multi-facility location-allocation proposed a model based on mini-max and Tabu search heuristic.

2.3 Minimax facility location model

Minimax is a facility location problem to locate a given number of (emergency) facilities anywhere along a road network so as to minimize the maximum distance between these facilities and fixed demand locations assigned to them (Garfinkel et al. 1977; Drezner and Wesolowsky, 1991). Minimax has been applied to wide range of problem settings such as the m-center problem (Garfinkel et al. 1977), vehicle routing (Golden et al. 1997), industrial pollution control (Sakava and Yano, 2012), portfolio selection (Teo and Yang, 2001; Deng et al. 2007), among others. Exact solution of minimax location problem is NP hard and estimation is non-deterministic, where the error is found to be very small. As our goal is to minimize the distance from every demand point to its nearby facility and to minimize sum of initial setup costs of these facilities, we have considered Euclidean distance. The objective function would be:

$$\text{Min}\, f\left(X_1,\ldots,X_m\right) \qquad (1)$$

Where $f\left(X_1,\ldots,X_m\right)=\max\left\{\max_{1\le j<k\le m} v_{jk}d\left(X_j,X_k\right),\max_{\substack{1\le i\le n\\1\le j\le m}} w_{ji}d\left(X_j,P_i\right)\right\}$

Where v_{jk} is the weight between new facilities; and w_{ji} is the weight between new facility and existing facility. Also, $d\left(X_j,X_k\right)$ is the distance between new facilities and $d\left(X_j,P_i\right)$ is the distance between new and existing facilities. N and M are number of existing and new facilities respectively.

2.4 Tabu search heuristic for facility location

Tabu search is a metaheuristic approach introduced by Glover (1989) to overcome local optimality entrapment by exploring the solution space beyond local optimal solution (Skorin-Kapov & Skorin-Kapov, 1994; Al-Sultan & Al-Fawzan, 1999; Sun, 2006; Klincewicz, 1992). Tabu search has successfully been applied to a wide range of problem settings such as vehicle routing (Taillard et al. 1997), Job shop scheduling

(Pezzella & Merelli, 2000), assignment problem (Skorin-Kapov, 1990; Chakrapani & Skorin-Kapov, 1993; Dıaz & Fernández, 2001), architectural design (Lee & Koh, 1997), graph partitioning (Rolland et al. 1996), time tabling problem (Burke et al. 2003; Burke et al. 2007; Lü & Hao, 2010), the capacitor placement problem (Huang et al. 1996), facilities location problem (Sun, 2006; Ghosh, 2003; Arostegui et al. 2006), among others. For determining the potential sites for temporary location of blood centers a step-by-step methodology has been devised. The steps for applying Tabu search heuristics are as follows: (1) Initialize the mandatory solution; (2) explore all possible relocations (3) If the current move results in a solution better than the best known solution, the result is executed. Else, choose and execute the best move that does not involve any locations in the Tabu list; (4) updating the best-known solution; (5) getting the coordinates for location of temporary facilities.

2.5 Application of Multi-Criteria Decision Making in facility location

Since the introduction of multi-criteria decision making (MCDM) to management sciences research, these methodologies have also been successfully applied in facility location problems. In the MCDM methodologies, the decision maker selects the best-predetermined alternative according to the priority of each criterion and the interactions or inter-relations between the criteria. The popular MCDM techniques are Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Simple Additive Weighting (SAW), Hierarchical Additive Weighting, Elimination and Choice Expressing Reality (ELECTRE), Technique for Order Preference by Similarity to Ideal Solution) (TOPSIS), among others. The amount of literature dealing with facility location problem by employing MCDM approaches has been found to have substantial growth in the last decade. We have conducted a thorough review of literature on facility location problems employing MCDM approaches in large-scale emergency situations and tabulated the same in Table 3.

Table 3: Application of MCDM in facility location during emergent situations

Citation	**Overall Research Focus**	**Methodology Used**
Ishizaka & Labib (2014)	Evaluation and Prevention of Disasters	Analytic Hierarchic Process
Vafaei & Oztaysi (2014)	Selecting the field hospital place for disasters	Fuzzy AHP and Fuzzy TOPSIS
Yang et al. (2015)	Disaster recovery site selection	DEMATEL and ANP

Roh et al. (2015) Bozorgi-Amiri & Asvadi (2015)	Prepositioning of warehouses for humanitarian relief operations Locating relief logistics centers during disaster periods	Fuzzy AHP and Fuzzy TOPSIS AHP
Rezaei-Malek et al. (2016)	Relief pre-positioning in disaster	PROMETHEE
Celik (2017)	Location of temporary shelters for disaster relief operations	DEMATEL

3. Model formulation

We have formulated the problem into a mathematical model by taking various costs and constraints into account. The notations used in the mathematical formulation; assumptions and constraints are given below

Notations

In this model formulation Notations used are:

i	Number of Existing Facilities, $i \in I = \{1,...,m\}$
j	Number of New Facilities, $j \in J = \{1,...,n\}$
k	Number of New Facilities, $k \in K = \{j,...,n\}$
F	Facility fixed cost
N	Total number of units
C	Unit Cost
T_c	Transportation cost per unit
M	Maintenance cost
D	Distance from existing facilities
a_i, b_i	Coordinates of Permanent Blood Centers
c_i, d_i	Coordinates of Hospitals part type j
w_{ji}	Weighted constant between Permanent and Temporary Blood Centers
u_{ji}	Weighted constant between Hospitals and Temporary Blood Centers
x_i, y_i	Coordinates of Temporary Blood Centers

Assumptions and Constraints

Model is formulated keeping in mind some assumptions.

- Hospitals and Blood center locations are known.
- Euclidean Distances are considered.
- Number of temporary facilities to be located is known.
- No Obstruction is there while locating new facilities.

The constraints of the problem include:

- Objective function should be greater than the minimum distance between any facilities.
- Objective function should be convex function.

The main objective is to determine the potential sites for temporary location of blood centers in disaster conditions that could serve the hospital with minimum response time. The various steps for model formulation are as follows:

Step 1: Collect the input data required

- All the Coordinates for Permanent Blood Centers
- All the Coordinates for Hospitals
- Weighted constant between Permanent and Temporary Blood Centers
- Weighted constant between Hospitals and Temporary Blood Centers

Step 2: Define objective function

The objective here for the study is to determine the potential sites for temporary location of blood centers by minimizing the maximum distance between hospitals and temporary blood centers. The objective function should be minimized in order to obtain optimal solution.

The objective function:

$$\min\left\{\max\left\{v_{jk}\left[\left(X_j - X_k\right)^2 + \left(Y_j - Y_k\right)^2\right]^{1/2}, u_{ij}\left[\left(X_j - c_i\right)^2 + \left(Y_j - d_i\right)^2\right]^{1/2}\right\}\right\} \qquad (2)$$

Objective function includes the distance between new facilities, distance between hospital and temporary blood centers with the following constraints (1) objective function should be greater than the distance between new facilities; (2) objective function should be greater than the distance between permanent blood centers and temporary blood centers.

3.1 Model formulation

Here we have given the model formulation for determining the optimal number of temporary blood facility.

Assumptions

Model is formulated keeping in mind some assumptions. Assumptions used in this problem are:

- Hospitals and Blood center locations are known.
- Euclidean Distances are considered.
- No Obstruction is there while locating new facilities.

The objective is to determine the optimal number of temporary blood centers in disaster conditions that could serve the hospital with minimum response time. Steps for model formulation are:

Step 1: Collect the input data required

- All the Coordinates for Permanent Blood Centers
- All the Coordinates for Temporary Blood Centers
- Facility fixed cost
- Total number of units
- Unit Cost
- Distance from existing facilities
- Transportation cost per unit
- Maintenance cost

Step 2: Define objective function

The objective here for the study is to determine the optimal number of temporary blood centers by minimizing the total cost required in establishing, maintaining, ordering and transportation cost.

The objective function:

$$Z = \min\left\{\left(j * f\right) + \left(C * N / j\right) + \left(D * T_c\right) + \left(j * M\right)\right\} \quad (3)$$

The objective function should be minimized in order to obtain optimal solution.

Objective function includes:

Fixed Cost $(j*f)$

Part Cost $(C*N/j)$

Transportation Cost $(D*T_c)$

Maintenance Cost $(j*M)$

Constraint: distance should be calculated from all the existing facilities.

3.2 Procedure for determining optimal number of temporary blood facility

Here we are determining the optimal number of temporary blood centers using the different cost components such as fixed cost, part cost, transportation cost and maintenance cost. For each number of facilities to be allocated, we calculate the total cost for locating temporary blood centers. The distance will be calculated between the existing blood centers and the temporary blood centers. For determining the optimal number of temporary blood center, a step-by-step methodology was devised. The methodology is depicted in Figure 1.

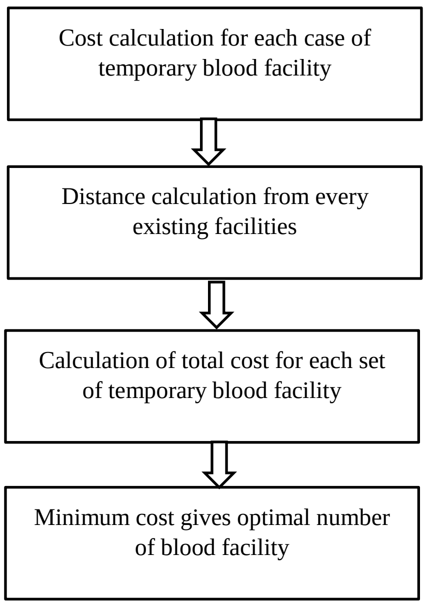

Figure 1: Temporary blood facility location allocation procedure

4. Ranking the temporary blood facility location factors using Bayesian Network

It is critical to model the effect of each facility location criteria on different cost elements as most of the criteria are uncertain and can easily fluctuate before and after decisions (Snyder, 2006; Dogan, 2012; Xu et al. 2010). Failure to precisely represent the influence of each temporary blood facility location criteria and understand uncertainties during and post-disaster periods results in strategic mistakes that are difficult to overcome. There will be limited and incomplete data related to human injuries and the demand for blood during and after disaster. Therefore, there is a need for a complete and efficient method to encode human belief by following a systematic approach while considering all the relations among factors of temporary location of blood facility, as well as between factors and their cost measures. A Bayesian network (BN) is a probabilistic graphical method that represents set of conditional dependencies (causality) between factors in an efficient, intuitive, and propagating the uncertain and ambiguous information in a transparent way. The concept of BN was introduced as a technique to apply the conditional probability to elicit information from experts, and provide a structure guide to efficient reasoning, even with incomplete knowledge (Chin et al. 2009; Nepal et al. 2014). Figure 2 explains the concept and steps of Bayesian networks. A sample Bayesian Network is given in Figure 3.

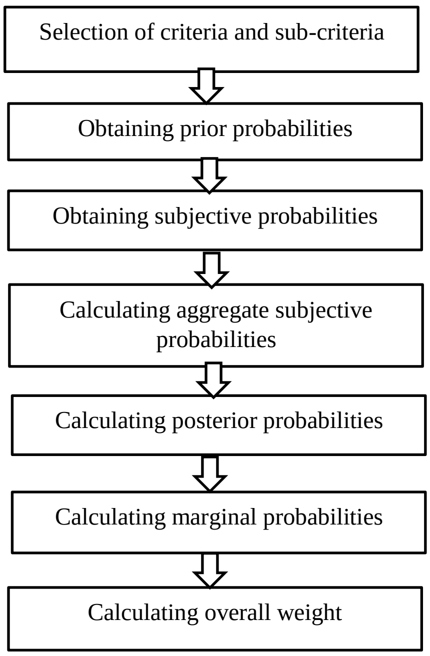

Figure 2: Bayesian Belief Methodology

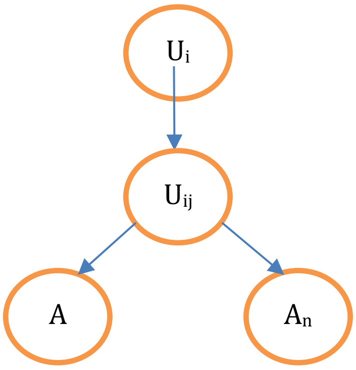

Figure 3: A sample Bayesian Network

In the Figure 3, the variable U_{ij} is influencing statistical independent variables A_m and A_n. While, variable U_{ij} is in turn dependent on U_i. Unidirectional arrows from one node to another show the relationships between the nodes. Bayes theorem (see equation 4) is used to get posterior probabilities of the evidence variables with respect to any query variable in the network, and the marginal probabilities by equation (6)

$$P(A_m/U_{ij}) = \frac{P(U_{ij}/A_m)P(A_m)}{\sum_{m=1}^{n} P(U_{ij}/A_m)P(U_{ij})} \tag{4}$$

$$P(U_{ij}/U_i) = \frac{P(U_i/U_{ij})P(U_{ij})}{\sum_{j=1}^{v} P(U_i/U_{ij})P(U_{ij})} \tag{5}$$

for all U_i and, the marginal probabilities are calculated as

$$P(A_m) = P(A_m/U_{ij}).P(U_{ij}) + P(A_m/U'_{ij}).P(U'_{ij}) \tag{6}$$

$$P(U_{ij}) = P(U_{ij}/U_i).P(U_i) + P(U_{ij}/U'_i).P(U'_i) \tag{7}$$

Where n is total number of sub-criteria and v represents the number of criteria. The term $P(U_{ij}/U_i)$ represents the importance of U_{ij} given that objective of the problem is to optimize U_i. Similarly (A_m/U_{ij}) shows the importance of A_m given that the objective is to optimize U_{ij}. Conditional probabilities like $P(U_{ij}/U_i)$ and

$P\left(U_{ij} / A_m\right)$ represents the influence of sub-criteria on criteria and influence of criteria on objective function. These probabilities are subjective in nature and are obtained by expert opinion. Experts can use their experience or even look up historical data to provide these conditional probabilities values. For minimizing bias towards any particular attribute, it is advised to take opinion of multiple experts. It is also advised to use geometric mean for combining the individual judgment in group decision making scenario (Ramkumar and Jenamani, 2012; Ramkumar and Jenamani, 2015; Ramkumar et al. 2016; Ramkumar, 2016 Jharkharia and Shankar, 2007)

Along with the above-mentioned conditional probabilities, experts also provide prior probabilities for criteria and sub-criteria. Prior probability shows an initial assessment of the expert regarding the importance of an element towards the goal. Also expert needs to be selected based on their working area. Following steps are present in general to solve BBN:

- Problem should be clear and a network of criteria should be presented clearly. Dependencies should be clearly mentioned.
- This step is crucial. We need to assign a particular stage to each element. (Nepal et al. 2014) using three point Table as shown in Table 4. Three states to be considered are {x = Strong, Average, Null} for each element.

Table 4: Bayesian Utility Stages

x	**Utility Function:** Q_x
Strong	10
Average	5
Null	1

- Third step is to obtain expert opinion on the subjective conditional probabilities as mentioned before. These probabilities reflect the assessment given by an expert on the importance of any element with respect to one step higher criteria or sub-criteria. Since during initial stages it is not clear that whether a particular element turns out to be important or not so experts are asked to provide subjective probabilities for each state as shown in the equation below.

$$P(U_{ij}^{x} \mid A_m = x) = \{p_1 : strong, p_2 : average, p_3 : null\} \quad (8)$$

- So far, we have obtained subjective probabilities for three different states. We need to get a single value of subjective probability for our model. It can be obtained by using equation (9)

$$P\left(U_{ij} / A_m\right) = \frac{\sum_{x} Q_x . P\left(U_{ij}^{x} \mid A_m = x\right)}{\sum_{x=1}^{3} Q_x} \quad (9)$$

Here Q_x is the utility function as mentioned in Table 4 above. A similar method is used to obtain aggregate belief probabilities for sub-criteria given criteria.

- In the last step, we calculate posterior probabilities using equation (4). And lastly Marginal Probabilities are calculated by using equation (6). These values of marginal probabilities are final weights.

5. Case study

As for as location-allocation decision of temporary blood facilities during and post-disaster periods are concerned, the pollution and the company waste aspects of the industrial zone can affect the decision. Considering this important aspect, we are evaluating two cases by Bayesian Networks: (1) where the temporary blood facilities have to be located when the industries are not present in the city; (2) and where the temporary blood facilities have to be located when the industries are present in the city.

5.1 Data Collection

Getting real value data is very important considering the nature of this study. Full attempt has been made to collect actual data of the location of major hospitals and blood centers by surfing the websites and through Google Maps. We have chosen Jamshedpur city for our study, as it is the first planned industrial city of India with lot of Giants including Tata steel. Jamshedpur is the headquarters of the East Singhbhum district of Jharkhand State of India with a population of 1,337,131 according to 2011 census reports. Jamshedpur has been predicted as the 84th fastest growing city in the world for the timeframe of 2006-2020 with annual average growth rate of 2.59%. There are 23 major Hospitals and 5 major permanent Blood Centers in Jamshedpur city. This city is marked as vulnerable city towards natural disaster such as earthquake and floods. Recently, the city had a major earthquake measuring 6.9 rector scale. Similarly it had witnessed devastating floods during 2015. During and after the event the city needs to take care of its casualty. A complete list of these hospitals with location coordinates is given in Table 5 and the Figure 4 shows the Google maps for the same. A complete list of permanent blood centers in Jamshedpur city (India) is given in Table 6 and Figure 5 shows the Google maps for the same. For this study, Bayesian Belief Networks (BBN) has been used as solution methodology for ranking the temporary blood facility location factors. For this, we have taken the expert opinion of three managers from a permanent blood facility in Jamshedpur by administrating a questionnaire. We have used geometric mean for consolidating individual judgments into group decisions for BBN case. Experts have a long experience in the field of logistics

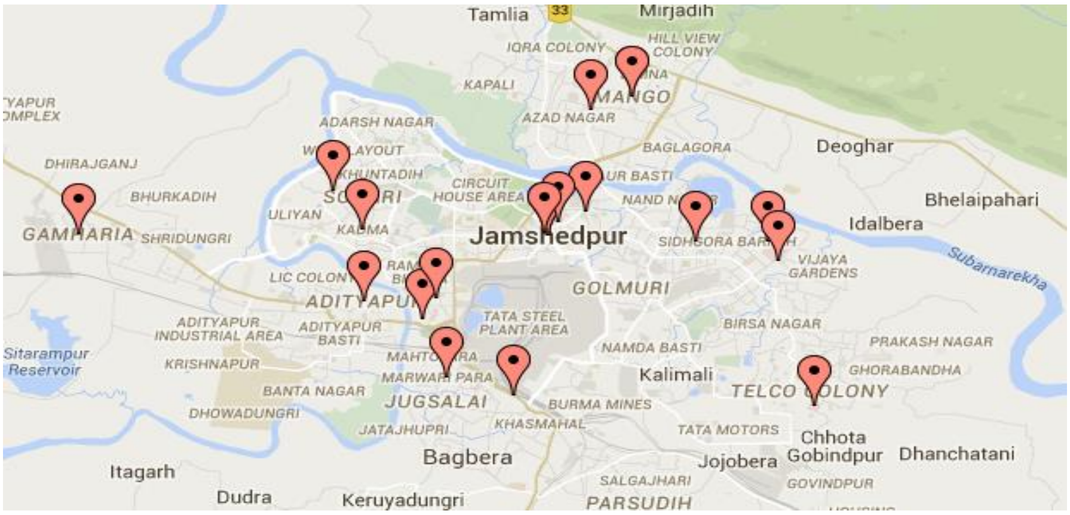

Figure 4: Location of Jamshedpur City Hospitals

Table 5: Location Coordinates of Jamshedpur hospitals

S.no.	Name of Hospitals	Coordinates	
		Latitude	Longitude

1	Adm Hospital Baridih	22.7993924	86.2488732
2	M G M Hospital	22.805182	86.202282
3	Mercy Hospital	22.8035553	86.2466664
4	ABC Health Care Centre	22.8076702	86.2048889
5	Medical Suprident Railway Hospital	22.8045665	86.2028754
6	RajsthanSevaSadan Hospital	22.7745229	86.1825876
7	Mehelbai Tata Memorial Hospital	22.8045665	86.2028754
8	Singhbhum Homeopathy Medical College & Hospital	22.770686	86.1961423
9	Sadar Hospital	22.805182	86.202282
10	Elite Hospital	22.834024	86.219577
11	Apex Hospital	22.8096824	86.210382
12	Brahmananda Narayana Multi Speciality Hospital	22.834024	86.219577
13	SidheshSwasthyaSevaShalyaPvt Ltd	22.7907697	86.1661178
14	Tata Main Hospital	22.791389	86.180556
15	Kantilal Gandhi Memorial Hospital	22.7869391	86.1778341
16	Tata Motors Hospital	22.8045665	86.2028754
17	Arogyam Hospital & Diagnostic Research	22.8034668	86.2323641
18	Gurunanak Hospital & Research Centre Pvt Ltd	22.8312131	86.2115448
19	Telco Hospital	22.7685113	86.2560149
20	Well View Health Research And Nursing Centre Private Limited	22.805182	86.202282
21	R S Trivedi Memorial Hospital& Advanced Orthopadiac Center	22.805833	86.165833
22	BhartiyaYugvasistaBrahamanandaSangh	22.8141859	86.1598882
23	Vanguard Hospital	22.8049785	86.1090119

Figure 5: Permanent blood centers Location of in Jamshedpur (India)

Table 6: Location Coordinates of Permanent Blood Centers/ Facilities in Jamshedpur

S.No.	Name of Blood Centers	Coordinates	
		Latitude	Longitude

1	Indian Red Cross Society	22.791389	86.180556
2	MGM Blood Bank	22.805182	86.202282
3	Arogyam Hospital & Diagnostic Research Centre	22.8034668	86.2323641
4	Jamshedpur Blood Bank	22.8147227	86.2652444
5	Blood Bank Jamshedpur	22.79296	86.1790513

5.2 Locating the Temporary Blood Centers by Tabu Search

In this section, we explain the model shown in Section 2 by Tabu Search Heuristic. All computation experiments were conducted in Matlab 14a on a laptop with Intel Core i5, 2.2 GHz and 6 GB of RAM. All the assumptions provided in Section 2 are considered for temporary location-allocation decisions of blood centers. The inputs for our model are (1) location coordinates of hospitals; (2) location coordinates of permanent blood centers; (3) distance between the temporary blood centers; (4) distance between temporary blood centers and permanent blood centers; and (5) distance between temporary blood centers and Hospitals

We have applied Tabu search heuristic for locating the temporary blood centers with the following assumptions: (1) Euclidean Distances are considered; (2) No Obstruction is there while locating new facilities. We have located 6 temporary blood facilities/ centers by utilizing the Tabu search heuristic. Table 7 shows the coordinates for the temporary blood centers which are to be located in Jamshedpur city which will be useful during and post-disaster periods. In the Figure 6, the square markers are the located temporary blood banks, and rest is hospitals. The arrow shows the allocation of the hospitals to the temporary blood centers.

Table 7: Location decision of temporary blood center using Tabu Search heuristic

S.no.	Temporary Blood Centers	Coordinates	
		Latitude	Longitude
1	Temporary Blood Center 1	22.8176	86.1681
2	Temporary Blood Center 2	22.7764	86.1864
3	Temporary Blood Center 3	22.8002	86.2836
4	Temporary Blood Center 4	22.8138	86.1713
5	Temporary Blood Center 5	22.7928	86.205
6	Temporary Blood Center 6	22.8426	86.2041

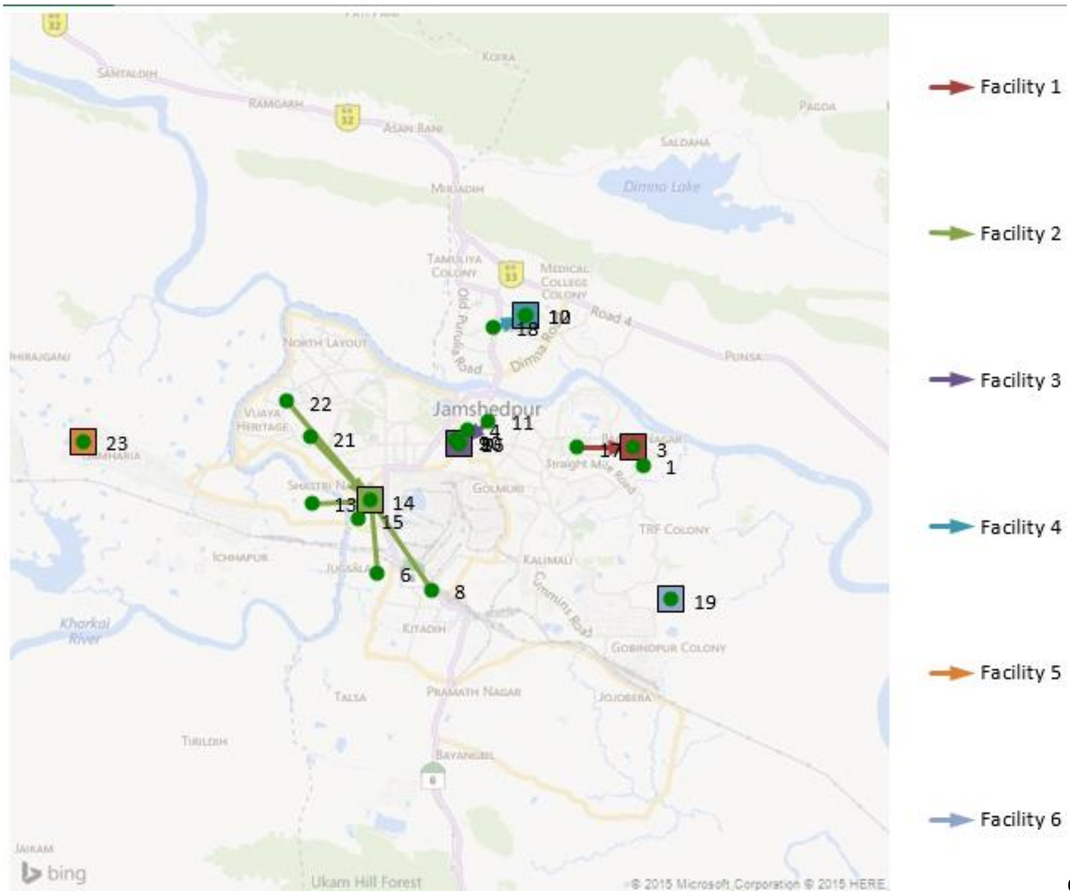

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Figure 6: temporary blood facilities Location-Allocation

5.3 Determining the Optimal Number of Blood Centers

We have followed the methodology as discussed in Figure 1 for determining the optimal number of temporary blood centers during and post-disaster periods in Jamshedpur city. We have taken fixed facility cost as Rs. 10,000; transportation cost as Rs. 12/ Km and maintenance cost as Rs. 500 in this case after discussing with the permanent blood center experts in Jamshedpur. On the basis of minimum total cost, we determine the optimal number of temporary blood banks during and post-disaster periods. Figures 7 (a) to 7 (f) presents the different locations-allocation decisions for different number of temporary blood banks. The total cost with respect to number of temporary blood facility is given in Table 8. We conclude that there must be six temporary blood centers in the city as the total cost is less comparing to other cases (see Table 8).

Figure 7 (a): Three Temporary blood centers Location-Allocation

Figure 7 (b) Four Temporary blood centers Location-Allocation

Figure 7 (c) Five Temporary blood centers Location-Allocation

Figure 7 (d) Six Temporary blood centers Location-Allocation

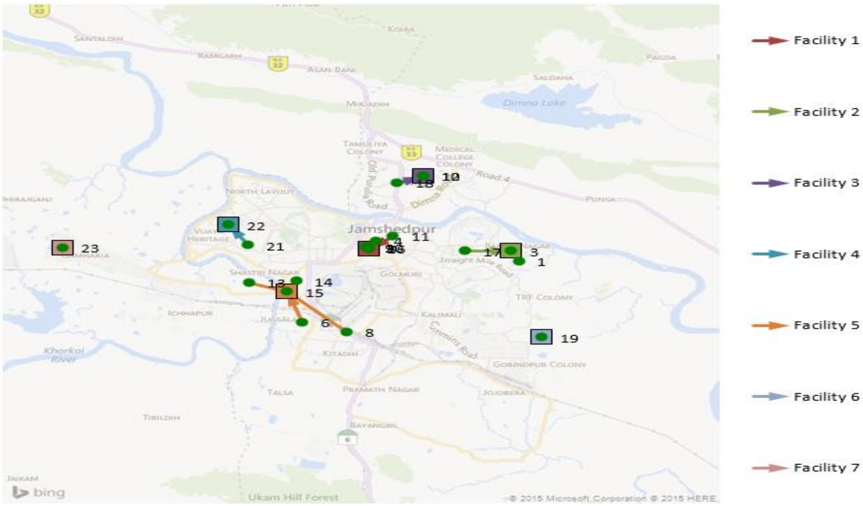

Figure 7 (e) Location-Allocation Decision for Seven Temporary blood centers

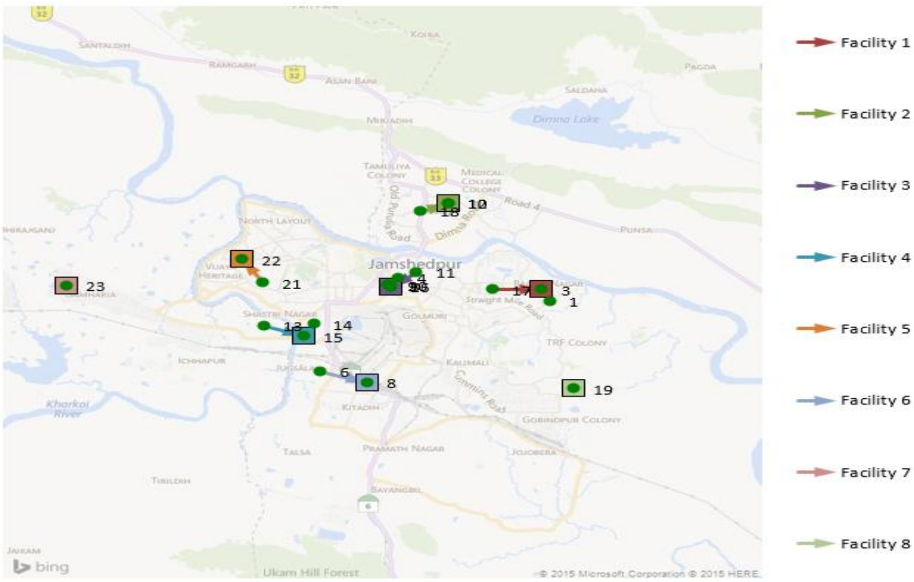

Figure 7 (f) Location-Allocation Decision for Eight Temporary blood centers

Table 8: Temporary blood centers location costs

S.No.	Number of Temporary Blood Centers	Total Cost
1	Three	101913.6
2	Four	126656.0
3	Five	91285.00
4	Six	88077.60
5	Seven	89334.40
6	Eight	94698.80

5.4 Ranking the temporary blood facility location factors using Bayesian Network

We have used Bayesian Belief Networks (BBN) as solution methodology for prioritizing and ranking the temporary blood facility location factors based on expert opinion. The industrial presence effects the location-allocation decisions of temporary blood facilities during and post-disaster periods. So, here we are considering two cases: (1) where the temporary blood facilities have to be located in the city, when the industries are not present in the city; (2) and where the temporary blood facilities have to be located, when the industries are present in the city. We have identified 15 such driving factors for the case 1 where industries are not present and group them into three major criteria that can help in location-allocation decisions (see Figure 8). We have identified 20 such driving factors for the case 2 where industries are present and group them into four major criteria (see Figure 9). The criteria and Sub-Criteria has been selected through thorough literature review.

We have collected data from three experts with a strong expertise in the field of logistics and warehousing from a permanent blood facility in Jamshedpur. In order to remove the bias in individual decision-making, we use geometric mean for consolidating individual judgments into group decisions. Two types of data have been collected from experts: (1) prior probabilities of criteria and sub-criteria; (2) subjective probabilities (conditional probabilities of criteria given a sub-criterion). In our case prior probabilities represents the probability that a particular sub-criteria or criteria are responsible for finding a location. For instance, what is the probability that the presence of highways is essential for finding warehousing site? Expert gives his/her opinion in terms of percentage for each of the level (strong, average and null). Strong means great importance while null means no or minimal importance. For subjective probability, experts have been asked about the percentage of importance (in terms of strong, average and null) of criteria if prior probability of sub-criteria is strong, average, and null. Table 9 and Table 10 show the prior probabilities for sub-criteria and criteria. Due to brevity, we have given only the calculation for the scenario where the industries are not present.

Table 11 depicts the data for conditional probabilities for Subjective probabilities of criteria given a sub-criterion at state *x*. For example, P(U11| A1 = Strong) is estimated to be at strong with 0.6 probability, and that at average and null with probabilities 0.25and 0.15, respectively. It is important to note that the sum of the probabilities across the states equals 1. The multistate belief probabilities in Table 8 were converted into their respective aggregated belief values by using the utility function given in (equation 8). Table 12 depicts the aggregated values of belief probabilities of criteria given a sub-criterion for the case when industries are not present in the city. Due to brevity, we have not given the aggregated belief probabilities calculation for the scenario where the industries are not present.

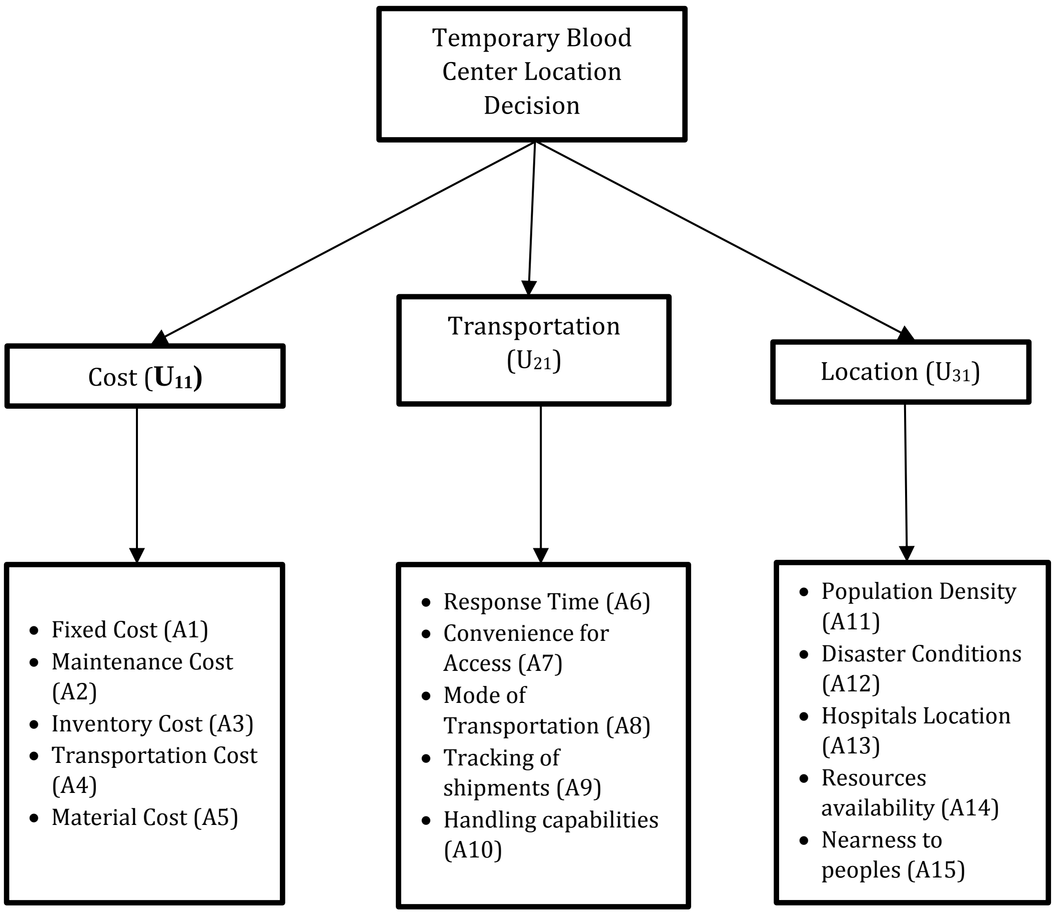

Figure 8: Criteria for locating the temporary blood facilities without companies

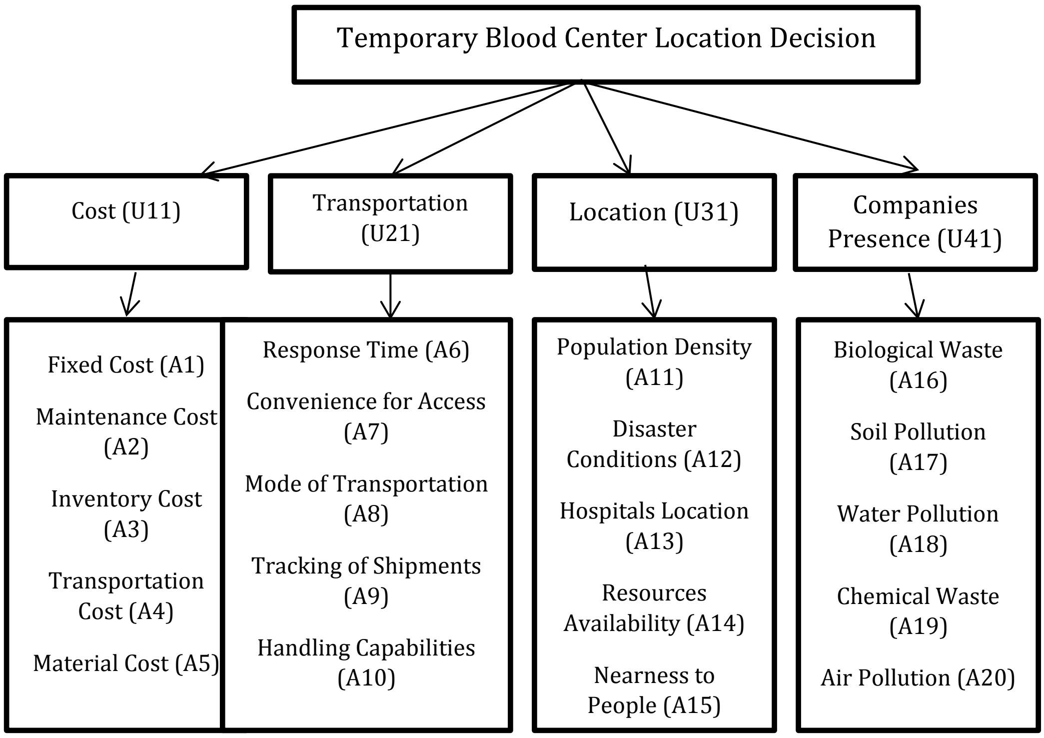

Figure 9: Criteria for locating temporary blood facilities including companies

Table 9: Sub-Criteria of Prior Probabilities without companies

Sub-Criteria	**Strong**	**Average**	**Null**
A1	0.5	0.3	0.2
A2	0.2	0.25	0.55
A3	0.15	0.25	0.6
A4	0.2	0.3	0.5
A5	0.7	0.2	0.1
A6	0.8	0.15	0.05
A7	0.6	0.25	0.15
A8	0.1	0.15	0.75
A9	0.1	0.1	0.8
A10	0.4	0.4	0.3
A11	0.6	0.3	0.1
A12	0.85	0.1	0.05
A13	0.6	0.3	0.1
A14	0.6	0.25	0.15
A15	0.65	0.25	0.1

Prior probabilities for sub-criteria at state x (x = strong, average, null)

Table 10: Prior Probabilities for Criteria without companies

Sub-Criteria	**Cost**	**Transportation**	**Location**
Strong	0.6	0.7	0.5
Average	0.25	0.25	0.3
Null	0.15	0.05	0.2

Prior probabilities for sub-criteria at state x (x = strong, average, null)

Table 11: Subjective probabilities of criteria given a sub-criterion at state *x* (without companies)

Sub-Criteria		$P(U_{11}^{x}\backslash A_i)$			$P(U_{21}^{x}\backslash A_i)$			$P(U_{31}^{x}\backslash A_i)$		
		Strong	Average	Null	Strong	Average	Null	Strong	Average	Null
A1	Strong	0.6	0.25	0.15	0.4	0.3	0.3	0.5	0.3	0.2
	Average	0.5	0.3	0.2	0.35	0.35	0.3	0.4	0.4	0.2
	Null	0.4	0.35	0.25	0.3	0.5	0.2	0.3	0.3	0.4
A2	Strong	0.3	0.35	0.35	0.3	0.3	0.4	0.2	0.2	0.6
	Average	0.2	0.2	0.4	0.25	0.3	0.45	0.05	0.25	0.7
	Null	0.15	0.35	0.5	0.1	0.5	0.4	0.2	0.25	0.55
A3	Strong	0.1	0.3	0.6	0.25	0.2	0.55	0.5	0.3	0.2
	Average	0.2	0.4	0.4	0.2	0.5	0.3	0.4	0.4	0.2
	Null	0.3	0.35	0.45	0.1	0.35	0.55	0.3	0.4	0.3
A4	Strong	0.2	0.3	0.5	0.1	0.6	0.3	0.4	0.4	0.2
	Average	0.25	0.35	0.4	0.7	0.25	0.05	0.45	0.3	0.25
	Null	0.2	0.3	0.5	0.6	0.25	0.15	0.4	0.35	0.25
A5	Strong	0.8	0.15	0.05	0.55	0.3	0.15	0.2	0.3	0.5
	Average	0.6	0.2	0.2	0.3	0.4	0.3	0.4	0.3	0.3
	Null	0.5	0.3	0.2	0.2	0.5	0.3	0.2	0.5	0.3
A6	Strong	0.85	0.1	0.05	0.5	0.4	0.1	0.4	0.3	0.3
	Average	0.7	0.2	0.1	0.8	0.15	0.05	0.35	0.35	0.3
	Null	0.5	0.3	0.2	0.6	0.2	0.2	0.3	0.5	0.2
A7	Strong	0.5	0.3	0.2	0.6	0.3	0.1	0.5	0.4	0.1
	Average	0.4	0.4	0.2	0.85	0.1	0.05	0.8	0.15	0.05
	Null	0.4	0.3	0.3	0.7	0.2	0.1	0.7	0.2	0.1
A8	Strong	0.2	0.3	0.5	0.5	0.3	0.2	0.3	0.2	0.5
	Average	0.25	0.35	0.4	0.2	0.3	0.5	0.4	0.4	0.2
	Null	0.1	0.2	0.7	0.15	0.25	0.6	0.4	0.4	0.2

A9	Strong	0.15	0.25	0.6	0.2	0.3	0.5	0.1	0.4	0.5
	Average	0.1	0.3	0.6	0.1	0.55	0.35	0.1	0.3	0.6
	Null	0.05	0.25	0.7	0.15	0.25	0.6	0.1	0.2	0.7
A10	Strong	0.5	0.3	0.2	0.1	0.3	0.6	0.05	0.15	0.8
	Average	0.45	0.25	0.3	0.1	0.5	0.4	0.1	0.2	0.7
	Null	0.35	0.3	0.35	0.05	0.15	0.8	0.05	0.25	0.7
A11	Strong	0.7	0.25	0.05	0.3	0.3	0.4	0.4	0.3	0.3
	Average	0.5	0.3	0.2	0.3	0.2	0.5	0.2	0.55	0.25
	Null	0.4	0.4	0.2	0.1	0.1	0.8	0.15	0.25	0.6
A12	Strong	0.9	0.05	0.05	0.6	0.3	0.1	0.6	0.1	0.3
	Average	0.7	0.2	0.1	0.5	0.3	0.2	0.55	0.25	0.2
	Null	0.5	0.3	0.2	0.4	0.4	0.2	0.4	0.35	0.25
A13	Strong	0.6	0.3	0.1	0.6	0.1	0.3	0.3	0.6	0.1
	Average	0.4	0.4	0.2	0.55	0.25	0.2	0.2	0.5	0.3
	Null	0.3	0.3	0.4	0.4	0.25	0.35	0.15	0.45	0.4
A14	Strong	0.55	0.25	0.2	0.3	0.2	0.5	0.1	0.3	0.6
	Average	0.4	0.4	0.2	0.3	0.3	0.4	0.2	0.6	0.2
	Null	0.4	0.4	0.2	0.2	0.3	0.5	0.1	0.3	0.6
A15	Strong	0.6	0.2	0.2	0.3	0.2	0.5	0.3	0.2	0.5
	Average	0.5	0.2	0.3	0.1	0.4	0.5	0.3	0.3	0.4
	Null	0.3	0.4	0.3	0.2	0.2	0.6	0.2	0.5	0.3

Table 12: Aggregate Probabilities of a Criterion without companies Sub-Criterion

Sub-Criteria	$P(U_1\|A_i)$	$P(U_2\|C_i)$	$P(U_3\|C_i)$
A1	0.419	0.355	0.383
A2	0.276	0.297	0.205
A3	0.265	0.253	0.383
A4	0.264	0.417	0.382
A5	0.473	0.359	0.304
A6	0.497	0.500	0.355
A7	0.390	0.516	0.500
A8	0.236	0.314	0.298
A9	0.185	0.239	0.194
A10	0.377	0.189	0.150
A11	0.442	0.244	0.295
A12	0.502	0.429	0.416
A13	0.390	0.416	0.290
A14	0.397	0.296	0.263
A15	0.394	0.242	0.296

The next step is calculation of posterior probabilistic using Baye's Theorem (see equation 4). Table 13 and Table 14 shows the values of posterior probabilities of criteria given a sub-criterion for both cases where industries are not present and industries are present. These posterior probabilities are then used in next step to calculate marginal probabilities.

Table 13: Posterior Probabilities Calculation without companies criterion

Sub-Criteria	**U11**	**U21**	**U31**
A1	0.075	0.073	0.085
A2	0.028	0.035	0.026
A3	0.024	0.026	0.043
A4	0.028	0.051	0.051
A5	0.103	0.089	0.082
A6	0.118	0.135	0.104
A7	0.078	0.117	0.123
A8	0.016	0.024	0.025
A9	0.011	0.017	0.015
A10	0.064	0.036	0.031
A11	0.090	0.057	0.075
A12	0.122	0.119	0.125
A13	0.080	0.097	0.073
A14	0.079	0.067	0.065
A15	0.083	0.058	0.077

Table 14: Posterior Probabilities Calculation with companies sub-criterion

Sub-Criteria	U11	U21	U31	U41
A1	0.075	0.073	0.085	0.074
A2	0.028	0.035	0.026	0.031
A3	0.024	0.026	0.043	0.029
A4	0.028	0.051	0.051	0.031
A5	0.103	0.089	0.082	0.108
A6	0.118	0.135	0.104	0.110
A7	0.078	0.117	0.123	0.073
A8	0.016	0.024	0.025	0.020
A9	0.011	0.017	0.015	0.028
A10	0.064	0.036	0.031	0.081
A11	0.090	0.057	0.075	0.097
A12	0.122	0.119	0.125	0.067
A13	0.080	0.097	0.073	0.091
A14	0.079	0.067	0.065	0.101
A15	0.083	0.058	0.077	0.061
A16	0.067	0.114	0.074	0.108
A17	0.083	0.063	0.060	0.108
A18	0.056	0.125	0.072	0.135
A19	0.067	0.082	0.142	0.155
A20	0.080	0.080	0.058	0.075

Posterior probabilities are used as inputs for calculating marginal probabilities (see equation 6). These marginal probabilities are the final weights, which show the relative importance of sub-criteria with respect to our goal of location a temporary blood facility during and post-disaster periods. Table 15 depicts the marginal probabilities of sub-criteria when industries are not located in the city. Table 16 depicts the marginal probabilities of sub-criteria when industries are present in the city. Figure 10 and Figure 11 shows the overall weights for the factors in locating temporary blood facility during and post-disaster periods in both the cases.

Table 15: Marginal Probabilities of Sub-Criteria when the industries are not present in the city

Sub-Criteria	Marginal Probabilities
A1	0.078
A2	0.030
A3	0.030
A4	0.044
A5	0.092
A6	0.120
A7	0.106
A8	0.022
A9	0.015
A10	0.044
A11	0.073
A12	0.122
A13	0.084
A14	0.070
A15	0.072

Table 16: Marginal Probabilities of Sub-Criteria when the industries are present in the city

Sub-Criteria	Marginal Probabilities
A1	0.077
A2	0.030
A3	0.030
A4	0.040
A5	0.096
A6	0.117
A7	0.097
A8	0.021
A9	0.018
A10	0.053
A11	0.079
A12	0.108
A13	0.086
A14	0.078
A15	0.069
A16	0.092
A17	0.079
A18	0.099
A19	0.111
A20	0.074

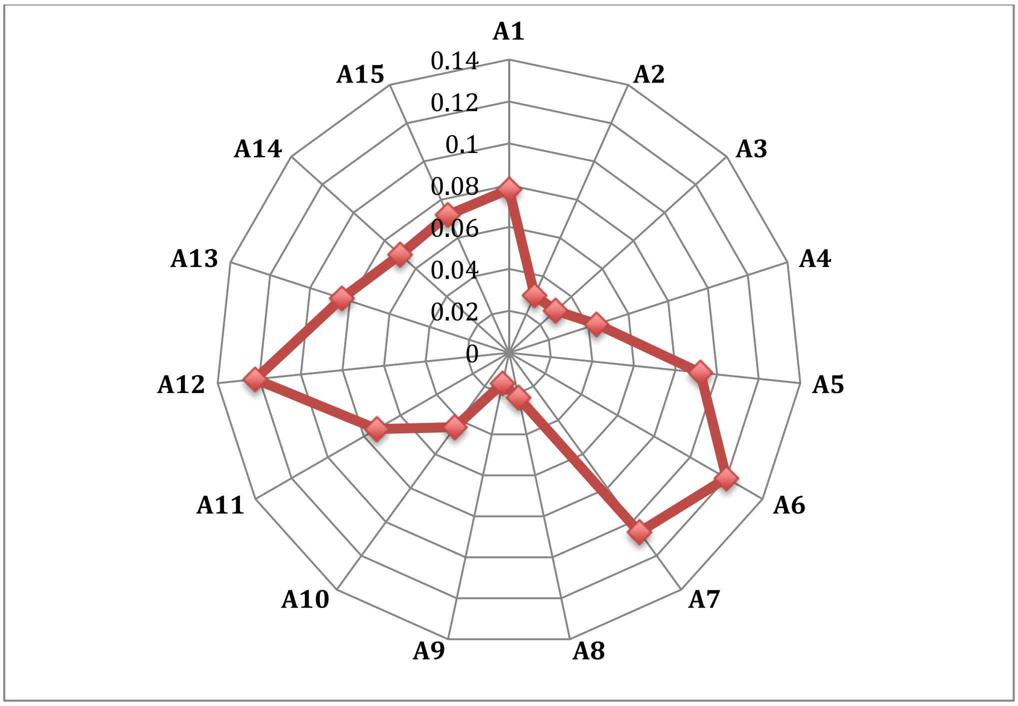

Figure 10: Overall weights for factors for locating temporary blood centers when industries are not present in the city

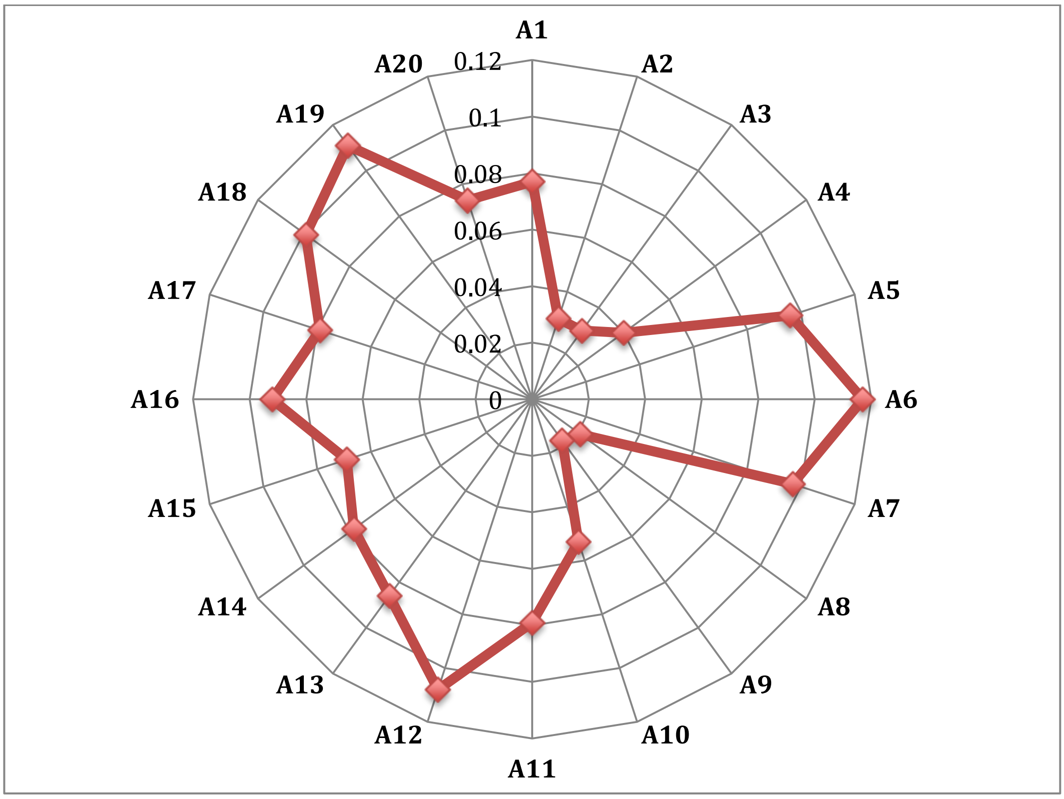

Figure 11: Overall weights for factors for locating temporary blood centers when industries are present in the city

6. Results and Discussions

As discussed in earlier sections, this study is on dynamic location-allocation decisions and near-optimal number of temporary blood centers to be required during and post-disaster periods in Jamshedpur city. This study also determines the important factors for locating the temporary blood facilities using two situations (1) when there is no industrial presence in the city; (2) there is industrial presence in the city. According to the empirical case study in section 5, our proposed models and methodologies provides few interesting results.

1. On the basis of minimum total cost, we conclude that the near-optimal number of temporary blood banks during and post-disaster periods in Jamshedpur city to be 6 (see Table 8). The total cost with respect to six temporary blood facility is 88077.60 Indian Rupees (INR). If we are increasing the facility from 6 to 7, the total cost found to be increasing to 89334.40 INR. Similarly, if we are decreasing the temporary blood facility from 6 to 5, we also found that the total cost is increasing from 88077.6 INR to 91285.00 INR. This shows that atleast 6 temporary blood facilities are required to satisfy the demand during and post-disaster periods. Figures 7 (a) to 7 (f) presents the different locations-allocation decisions for different number of temporary blood banks.

2. For the case of temporary location-allocation decisions when there is no presence of industries, the result suggests (see Table 15 and Figure 10) that past disaster conditions (A12) with a relative priority of 12.2% is the most important factor for goal of locating the temporary blood facilities during and post-disaster periods. The analysis also suggests that response time (A6) with a relative probability of 12%; convenience for access (A7) with a relative probability of 10.6%; material cost (A5) with a relative probability of 9.2%; and location of hospitals (A13) with a relative probability of 8.4% are the next most important factors.

3. For the case of temporary location-allocation decisions when there is presence of industries, the result suggests (see Table 16 and Figure 11) that response time (A6) with a relative priority of 11.7% is the most important factor for

goal of locating the temporary blood facilities during and post-disaster periods. The analysis also suggests that chemical waste (A19) with a relative probability of 11.1%; past disaster conditions (A12) with a relative probability of 10.8%; water pollution (A18) with a relative probability of 9.9%; convenience for access (A7) with a relative probability of 9.7%; and material cost (A5) with a relative probability of 9.6% are the next most important factors.

4. While Jabbarzadeh et al. (2014) focused on design of an emergency blood facility and Chen & Yu, (2016) designed a temporary facility location for the emergency medical services, our model gives an idea of 'how much temporary blood facilities are required in fulfilling the demand of blood during and post-disaster periods by taking the severity of the disaster into account.' This will help the blood banks to know 'where and to locate their temporary facilities and how much facilities are required to cope up during and post-disaster periods. We also determine the important factors for locating the temporary blood facilities under two situations; (1) when there is no industrial presence in the city; (2) there is industrial presence in the city.

5. As far as the developed economies are concerned, the private insurance companies contributes more in post-disaster reconstruction activities like temporary blood facility location. But, in case of emerging economies like India, the state and the individuals carry much of the costs of disaster (Kreimer & Arnold, 2000). The ad hoc funding further post pones the progress in post-disaster reconstruction activities in responding to disaster. Hence, at this moment, a study of dynamic temporary blood facility location-allocation decision during and post-disaster period is very much required at the emerging economies context by considering the optimal number of temporary blood facility to be located.

7. Conclusions

In this study, we have made the optimal temporary blood facility location-allocation decision based on minimax facility location model with Euclidean distance and Tabu search heuristic. We have identified the factors that are required for temporary blood facility location-allocation decisions during and post-disaster periods for the two above-mentioned cases by extant literature review. Since there is no pair-wise comparison between the sub-criteria like Analytic Hierarchy Process (AHP) or Analytic Network Process (ANP) in Bayesian Belief Networks (BBN); it effectively allows in capturing a strategic direction of the respondent while assigning conditional probabilities to criteria and sub criteria. Therefore, the benefit of BBN analysis is that it prevents an over-ranking or under-ranking purely based on pairwise comparison and deviating from strategic goals of the company. So we have used BBN for our study. The major contribution of this study are of three fold: (1) We proposed a multi-method framework based on Minimax facility location model and Tabu search for optimal location-allocation decision of temporary blood facility during and post-disaster periods. (2) We proposed a Bayesian Belief Network based framework for prioritizing the temporary blood facility location factors by taking the affect of industrial presence into account. (3) We applied the above-mentioned methods in a real life case study. The outcome of the BBN model presented here is purely dependent on the inputs provided by the experts of the case company. Further refinement of the model can also be done by additional field surveys and conducting the surveys in other locations.

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